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# Comparative Performance Evaluation of HEC-HMS and SWAT Models in Stream Flow Simulation: the Case of Bilate and Gidabo Watersheds, Ethiopia

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**ABSTRACT**

Many hydrological models have been developed to simulate watershed hydrology. However, identifying the most cost-effective and efficient hydrological models for a specific watershed with reasonable certainty becomes difficult. The purpose of this study was to compare the stream flow prediction efficiency of the HEC-HMS and SWAT models, as well as the associated uncertainty, in the Bilate and Gidabo watersheds. Model-sensitive parameters being identified, they were calibrated and validated. The parameter uncertainties were analyzed using Markov Chain Monte Carlo (MCMC) for HEC-HMS and Sequential Uncertainty Fitting version two (SUF-2) for SWAT. In the case of the HEC-HMS model, the results showed that constant loss rate (CR) was the most sensitive parameter, followed by lag time (LT) for both watersheds. SWAT detected ALPHA_BF in the Bilate Watershed and CN_2 in the Gidabo Watershed as the most sensitive parameters. Overall, both models could adequately simulate the hydrology of both watersheds. Despite their similar modeling capabilities, a comparison analysis revealed that the HEC-HMS model outperformed the SWAT model in simulating streamflow in both watersheds. The findings of this study can help potential model users make risk-informed decisions by selecting a representative model and quantifying associated uncertainty in the modeling field.

**Keywords:** Bilate and Gidabo watersheds, comparative evaluation, HEC-HMS, SWAT, flow simulation.

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## 1. INTRODUCTION

Many hydrological models had been developed and were accessible to water resources studies, such as water resources management, flood control, land planning, water quality, and climate change studies (Wu & Chen, 2015). The models were used to analyze the quantity of stream flow, reservoir system operation, surface and groundwater use management, flood forecasting, ecology, and a range of water management practices (Wurbs, 1998). According to a review of literature, the most commonly used hydrological models in Ethiopia were Hydrologiska Byran's Vattenbalansavdelning (HBV), Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS), Soil and Water Assessment Tool (SWAT), Hydrological Simulation Program-Fortran (HSPF), and MIKE SHE. However, the ranges of applications of the models were different since the assumptions involved in each model varied, and catchments were heterogeneous. Additionally, many models required data unavailable in the watersheds, especially in developing countries (Sivapalan et al., 2003). As a result, potential model users increasingly found it challenging to determine the best, most cost-effective, and most efficient hydrological models to produce high-quality results.

The hydrological model selection was based on knowledge of modeling method, data quality and availability, model performance, and applicability. Earlier studies conducted around the world indicated that one model might represent the hydrological/physical process better than the other. The performance of each model varied from watershed to watershed (Abebe, 2017; Abyot, 2008; Aliye et al., 2020; Dhami & Pandey, 2013; Golmohammadi et al., 2014; Khoi, 2016). Therefore, earlier studies suggested that further studies needed to reach a sound conclusion about the superiority of one model over the other.

HEC-HMS and SWAT models had been extensively used in different parts of the world. However, hydrological models were highly subject to uncertainty owing to the assumptions of the model itself and the watershed system complexities, which concerned potential model users (Song et al., 2015; Zhanling et al., 2009). Uncertainty in model output arose from measurement errors associated with input data, model structure, and parameter uncertainty (Abbaspour et al., 2007). From these uncertainty sources, uncertainty from parameters was easy to control through appropriate model calibration (Wu & Chen, 2015). However, parameter values obtained through the calibration process possessed a degree of quantifiable uncertainty because of incomplete knowledge of parameter value ranges, physical meaning, and temporal and spatial variability. Therefore, model predictions were unreliable when model parameter values were uncertain. In some cases, wastage of resources might occur due to overestimating uncertainty, and unexpected losses might occur due to underestimating uncertainty (Shen et al., 2012). Therefore, the uncertainty of hydrological models should be scrutinized (Abbaspour et al., 2007). In addition, Herrera et al. (2022) noted that when models are used to predict the future, it's crucial to limit the uncertainty of the outcomes.A variety of uncertainty analysis methods had been developed to characterize, control, and quantify the parameter and modeling uncertainties, such as sequential uncertainty fitting (SUFI-2), generalized likelihood uncertainty estimation (GLUE), Markov chain Monte Carlo (MCMC), and parameter solution (ParaSol). Among these methods, MCMC and SUFI-2 were widely used to quantify and control the uncertainty parameter in HEC-HMS and SWAT models. Abbaspour et al. (2007) stated that SUFI-2 was applied extensively to analyze the sensitivity of parameters and identify the critical source of uncertainty in watershed model outputs. MCMC was applied to quantify the uncertainty in modeling watersheds from model parameters. While HEC-HMS and SWAT models were widely used hydrological models, investigating the uncertainty assessment of the model was essential to improve the reliability of streamflow prediction.

The lack of data about the Ethiopian situation made hydrological modeling efforts challenging to manage water resources for sustainable development. Therefore, selecting models that require less data was economical and advantageous. Several hydrological modeling studies were conducted in Ethiopian watersheds. The HEC-HMS and SWAT models had been extensively used in different watersheds in Ethiopia (Abebe, 2017; Abyot, 2008; Aliye et al., 2020; Kassa & Forech, 2009). However, no exclusive studies were available on the suitability of these hydrological models in the Bilate and Gidabo watersheds. In light of this, the soil and water assessment tool (SWAT) and the hydrologic engineering centers-hydrologic modeling system (HEC-HMS) models are utilized in this work. Abyot (2008) suggested that the HEC-HMS model outperformed the RRL SMAR and RRL TANK models, capturing peak flow in both Bilate and Kulifo watersheds in the Abaya Chamo Basin. Kassa and Forech (2009) demonstrated that the models produced acceptable outputs in hydrological responses to land use and climate changes. They reported that the SWAT model outperformed the HSPF model when monthly and seasonal stream flow analyses were conducted. Abebe (2017) found that both SWAT and HBV-light models successfully predicted the discharge in the Geba Catchment. Similarly, Aliye et al. (2020) conclude that the HEC-HMS model outperformed other models in simulating the rainfall-runoff process. However, there appears to be no previous studies conducted on the Bilate and Gidabo watersheds using comparative hydrologic models,. As a result, the purpose of this research was to compare the performance and applicability of the HEC-HMS and SWAT hydrological models to the Bilate and Gidabo watersheds. This study sheds light on which model to use and establishes parameters for future use in the two watersheds. Future researchers, hydrologists, agronomists, and water resource managers may find this study useful in their future endeavors.

## 2. MATERIALS AND METHODS

### 2.1. Description of the study area

Bilate and Gidabo watersheds are among the major watersheds of the Abaya-Chamo sub- basin, the Rift Valley Lakes basin in Ethiopia. The geographical location of the Bilate Watershed is approximately between 6º40′0″N to 8˚5′00″ N latitude and 37º48′0″E to 38º 36′00″E longitudes. Similarly, the Gidabo Catchment is located between 6º15′0″and 6º55′0″N latitude and 38º15′0′′ to 38º40′0′′ E longitude.

Bilate River drains southwards into Lake Abaya in the main Ethiopian Rift Valley Basin (Figure 1). The study area of the Bilate Watershed covers an area of 5316km$^2$ at the entrance of Lake Abaya (outlet). The Bilate Watershed elevation ranges between 3329m a.m.s.l in the northern and 1193m a.m.s.l in the south with a mean elevation of 2261.5m a.m.s.l. The region drained by the Gidabo River is bordered by the southern part of the main Ethiopian Rift Valley Basin flowing eastwards into Lake Abaya (Figure1). The Gidabo Watershed lies in the Borena Zone of the Oromia Region, Gedeo Zone, and Sidama Region, Ethiopia. The estimated area of the Gidabo Watershed is 2310 km$^2$. The Gidabo Watershed area ranges between 1183 a.m.s.l near the outlet (at the Dam site) to 3173 a.m.s.l in the western part of the watershed with a mean elevation of 2261.5m a.m.s.l. The average mean maximum and minimum temperatures of Bilate are 32.6°C and 13.3°C, respectively. Moreover, for the Gidabo Watershed, the mean monthly temperature at the Gidabo Dam is 15°C to 30°C. The rainfall trend in both watersheds is bimodal.

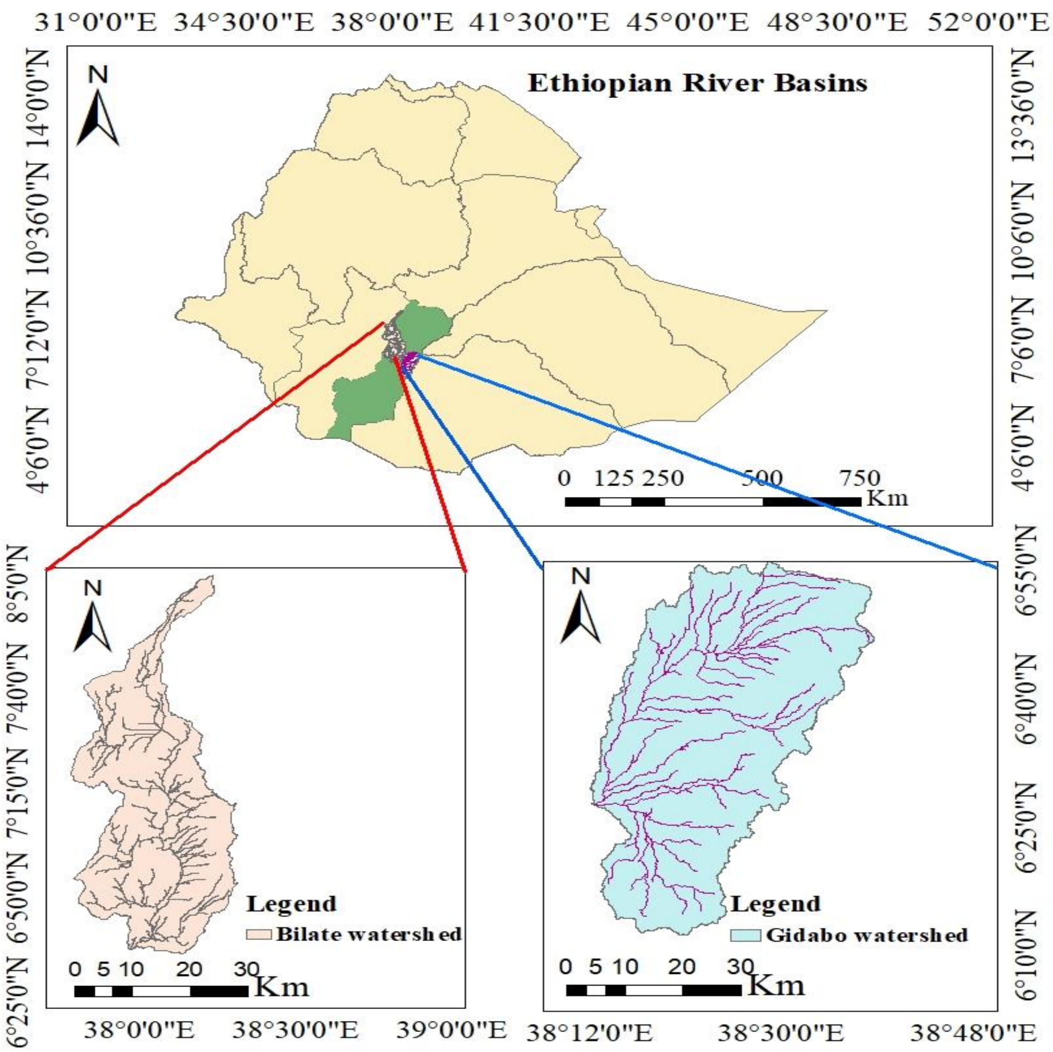



Figure 8. Location of study areas

## 2.2 Data Set

### *2.2.1. Meteorological data*

The National Meteorological Agency (NMA) of Ethiopia provided meteorological data for both the Bilate and Gidabo watersheds, including daily stream flow, daily minimum and maximum temperature, daily sunshine hourly, daily wind speed, and daily relative humidity. In this study, eight and three meteorological stations are available within and near the study area for the Bilate and Gidabo watersheds, respectively. The data was checked for homogeneity and consistency; errors were fixed, and insufficient and missing data were filled in. The study collected daily meteorological data from 1987 to 2016.

The SWAT model requires daily climate data of rainfall, maximum and minimum temperatures, wind speed, relative humidity, and solar radiation. The meteorological stations chosen for this study had daily air temperature and precipitation data. However, because they have comprehensive weather data, data from the Hosana and Dilla gauging stations in the Bilate and Gidabo watersheds, respectively, were used in this study.

#### *2.2.2. Stream flow*

Observed stream flow was required for calibration and validation of both the HEC-HMS and SWAT models. Bilate Tena and Measso are terminal gauging stations on the Bilate and Gidabo river basins, and stream flow data were collected from the Ethiopian Ministry of Water, Irrigation, and Energy. The data were collected over a 17-year period (1999-2015) for Bilate and a 10-year period (1997-2006) for the Gidabo Watershed.

#### *2.2.3. Digital Elevation Model*

Using DEM data as input, HEC-HMS, and SWAT models, the accumulation of flow and stream networks were calculated, and the watershed were divided into a number of sub-basins based on elevation. A DEM data with a resolution of 30mx30m was used here. A digital elevation model of both watersheds is provided in Figure 2.

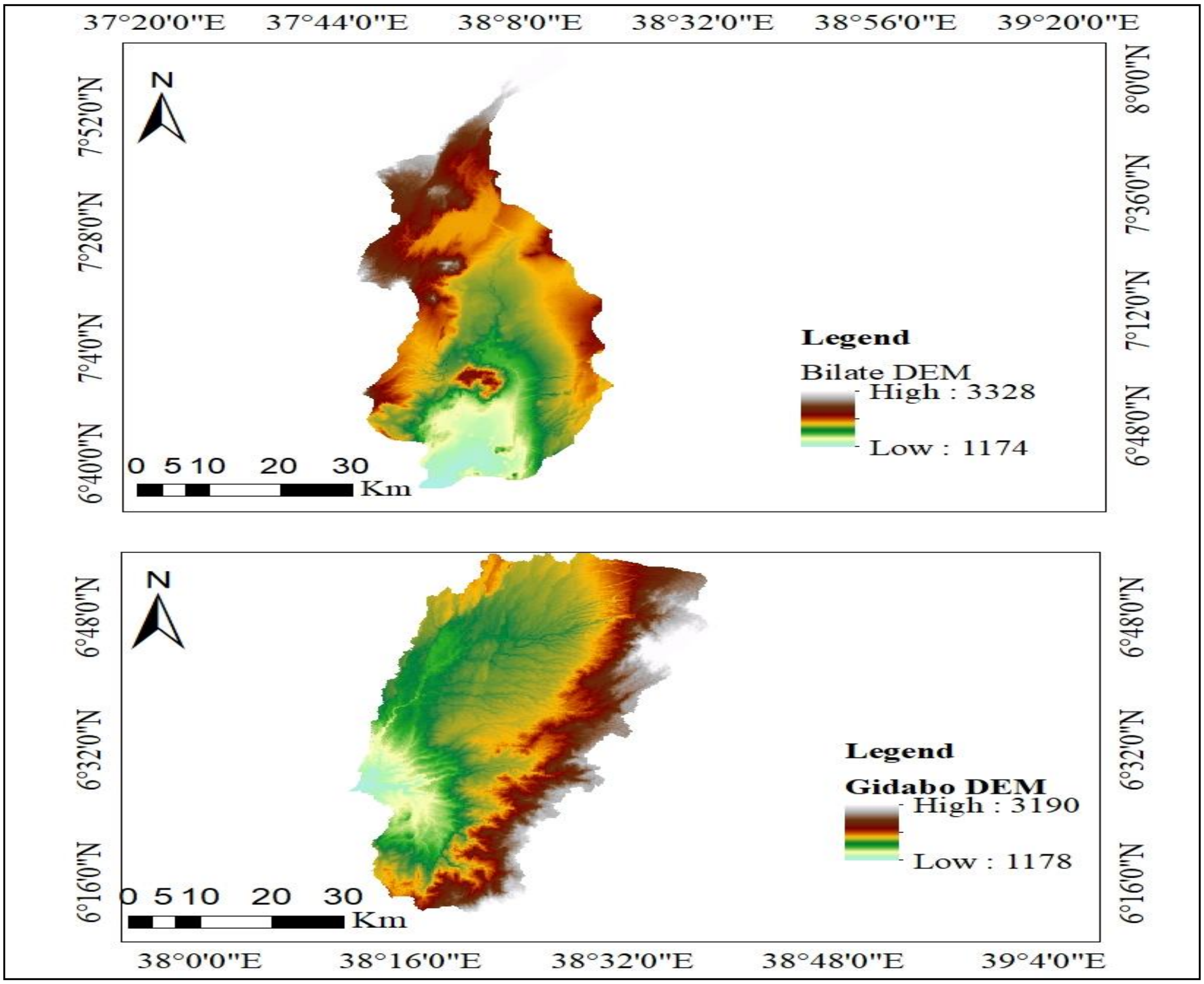



Figure 9: DEM of Bilate and Gidabo watersheds

The study areas' spatial and time series data were generated in the suitable model format and used in the model simulation. Using ArcGIS 10.3, a 30x30m DEM data resolution was used to delineate the watersheds at Bilate Tena and Measso gauging stations for Bilate and Gidabo watersheds, respectively. Accordingly, the entire Bilate and Gidabo watershed area were divided into 23 and 13 sub-basins, respectively. These sub-watersheds were further separated into Hydrologic response units (HRUs), a unique combination of soil, land use, land cover, and slope characteristic areas. The delineated watersheds are indicated in Figure 3.

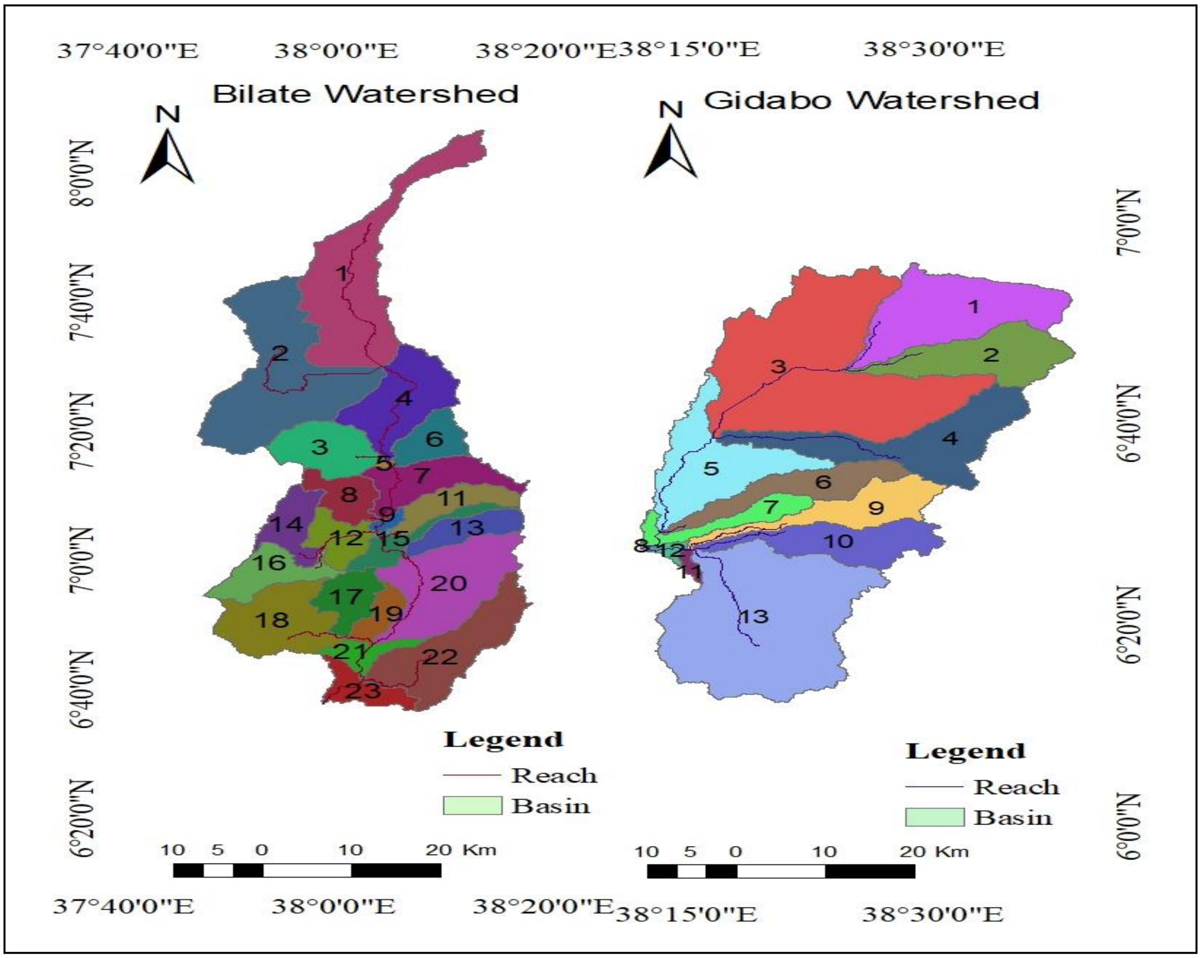



Figure 3: Bilate and Gidabo Watersheds

### *2.2.4. Land use and land cover*

Land use and land cover impact a runoff watersheds, surface erosion, and evapotranspiration. The map depicts the various land use/cover classes as well as the physical extent of the study areas. The land use/land cover map of the Bilate and Gidabo watersheds was created using Arc GIS 10.3 software. The predominant land cover in both watersheds is intensively cultivated land.

### *2.2.5. Soil data*

The Ethiopian Rift Valley Lake Basin Master Plan study was conducted in 2010, and soil samples were collected from all soil units of the basin. In this study, the soil data was collected from MoWIE. The Rift Valley Lake Basin Master Plan document was also used to get the soil information (Halcrow, 2010). 203 soil samples from 12 different soil units in the Rift Valley Basin were collected, and their physical and chemical characteristics were examined.

## 2.3. Hydrological Models

The HEC-HMS and SWAT hydrological models were used here in this study. The background information and the necessary steps used in the modeling processes are described in the following sections.

### *2.3.1. HEC-HMS hydrological model*

The Hydrologic Modeling System, HMS, was developed by the US Army Corps of Engineers Hydrologic Engineering Center (HEC) as a modeling tool for all hydrologic processes of dendritic watershed systems. It simplified complex tasks concerning hydrological studies, consisting of time series data, losses, runoff transform, open routing, rainfall-runoff simulation, and parameter estimation (Feldman, 2000; USACE, 2008). The HEC-HMS model is a physically based and conceptually semi-distributed model designed to simulate rainfall-runoff processes in many geographic areas, from large river basins to small urban and natural watershed runoffs. In addition, the HEC-HMS model uses a separate model that computes runoff, the base flow, and runoff volume. The model has four computation methods to address the responsiveness of watersheds, such as loss, transform, base flow, and routing.

The loss methods were designed either for event simulations or continuous simulations. The initial and constant loss methods were used to calculate the loss in the catchment, which was the maximum potential rate of precipitation loss constant throughout an event. These represented the physical properties of the watershed soil, land use, and antecedent condition (Razmkhah, 2016). HEC-HMS also had seven different transformation methods which simulated the process of the direct runoff from excess rainfall in a watershed. In this study, the Soil Conservation Service (SCS) Unit Hydrograph model was used to transform excess rainfall into runoff. The time of concentration (Tc) and lag time ($T_{lag}$) were employed in the transformation model to compute the runoff from excess rainfall.

The time of concentration was estimated based on the characteristics of the basin, including topography and the length of the reach, using Kirpich's method (Kirpich, 1940):

$$Tc = \frac{L^{0.77}}{S^{0.385}} \quad (1)$$

The lag time is computed as:

$$T_{lag} = 0.6 \times T_c \quad (2)$$

From different methods included in the model to compute base flow, the constant monthly base flow was selected in this study for its suitability to the study areas. The method used long-term simulations and required a separate monthly value for the overall simulation period. The average minimum flow value was taken before model calibration.

When runoff traveled through the channel reach, the flood became attenuated owing to channel storage effects. The Muskingum method of flood routing was selected in this study. It is often used for flood routing in natural channels (Sil et al., 2016). In this model, two parameters were calibrated: the coefficient K, which refers to the travel time of the flood wave through routing reach, and the dimensionless weighting factor (X), which corresponds to the attenuation of the flood wave as it moves through the reach. The Muskingum-Cunge routing equation is given by:

$$S_t = K[XI_t + (1 - X)Q_t] \quad (3)$$

where $S_t[L^3]$ is the storage; $I_t[L^3T^{-1}]$ is the inflow and $Q_t$ $[L^3T^{-1}]$ is the outflow from a given reach.

Arc hydro and HEC-GeoHMS were used to characterize the watersheds. HEC-GeoHMS mainly creates a basin model and a meteorological model and controls specifications before running the HEC-HMS model. The prepared basin model and features were taken as background input map files and imported to HEC-HMS 4.3. Since we had no observation stations in each sub-basin, the precipitation values were estimated by the most widely used Thiessen Polygon method, and weights were worked out in HEC-GeoHMS software.

**2.3.2. SWAT hydrological model**

The soil and water assessment Tool (SWAT) is a semi-distributed physically based model developed to estimate the stream flow, sediment, and chemical yields in basins. Streamflow generation is modeled along individual hydrologic response units (HRUs) using multiple watershed-scale characteristics such as hydraulic conductivity, available moisture content, pollutant loading, and management strategies. The HRU-scale results were then piled into sub-basin-scale outputs using appropriate weighted average procedures. The hydrological entities at the sub-basin levels were then routed separately. SWAT simulates surface runoff volumes and peak runoff rates for each HRU using daily or sub-daily rainfall levels. The SCS curve number and the Green Ampt infiltration methods are two methods available in SWAT to estimate surface runoff volume. It was challenging to apply the latter method since the sub-daily time step data criterion was difficult to obtain for the study watersheds. Therefore, the SCS curve number method was adopted in this study. SWAT model performs the essential water balance computation to estimate the different flux components given by Equation 4 (Neitsch et al., 2011) as:

$$\mathrm{SW}_t = \mathrm{SW}_o + \sum_{i=1}^{t}(\mathrm{R}_{day} - \mathrm{Q}_{surf} - \mathrm{Ea} - W_{seep} - \mathrm{Q}_{gw}) \quad (4)$$

where $SW_t$ is the final soil water content (mm), $SW_O$ is the initial soil water content (mm), $t$ is time (days), $R_{day}$ is the amount of precipitation on a day $i$ (mm), $Q_{surf}$ is the amount of surface runoff on a day $i$ (mm), $Ea$ is the amount of evapotranspiration on a day $i$ (mm), $W_{seep}$ is the amount of water entering the vadose level zone from the soil profile on day $i$ (mm), and $Q_{gw}$, is the amount of return flow on day $i$ (mm).

The model also calculates evaporation from the soil and plant canopy surface separately. The potential evapotranspiration (PET) and leaf area index (LAI), or the ratios of plant leaf area to the soil surface, are explicit functions of soil water evaporation. Depending on the input data available, the PET of the catchment could be computed using the Penman-Monteith, Priestley–Taylor or Hargreaves approaches. In the present study, the Penman-Monteith approach was used, which was given by (Allen et al., 1998):

$$ETo = \frac{0.408(Rnet-G)+\gamma\frac{900}{(T+273)}U(es-ea)}{\Delta+\gamma(1+0.34U)} \quad (5)$$

where, $ET_o$ is daily reference crop evapotranspiration [mm day$^{-1}$], *Rnet* is net radiation flux [MJm$^{-2}$day$^{-1}$], G is heat flux density in the soil [MJm$^{-2}$day$^{-1}$], $\gamma$ is psychometric constant [KPA°C$^{-1}$], U is wind speed measured at 2 m height [ms$^{-1}$]; $e_s$ is saturation vapor pressure $e_a = e_s$ * RH/100 [KPA], *RH* is relative humidity [%] and $\Delta$ is slope of the saturation vapor pressure curve [KPa°C$^{-1}$].

### 2.4 Model Sensitivity analysis

Sensitivity analysis determines how much a change in an input parameter affects the model response. Prior to assessing the major impact of input variability on certain model outputs of interest, the sensitive parameter was ranked. The output response changes when the most sensitive parameter is used. As a result, sensitivity analysis was used in this study to find sensitive model parameters and link them to catchment runoff generating features (Saltelli et al, 2000).

The sensitivity analysis was carried out manually in HEC-HMS to identify understand the most influential model parameter from selected key parameters. The SUFI-2, on the other hand, determines sensitivity for the SWAT model using global sensitivity analysis. The sensitivity ranks of parameters were assigned in the SUFI-2 method based on the p-value and t-stat values. Based on previous research on rainfall-runoff simulation using the SWAT model (Abebe, 2017; Aliye et al., 2020; Amaru Ayele & Gebremariam, 2020), key parameters were chosen to implement sensitivity and uncertainty analysis using the SUFI-2 model for both watersheds.

### 2.5. Model Evaluation and Statistical Analysis

Accuracy, consistency, and adaptability of hydrological models is essential for a better prediction of watershed responses. Therefore, the prediction efficiency criterion is required to assess the performance of the model. The performance of HEC-HMS and SWAT models was evaluated in terms of coefficient of determination ($R^2$), Nash and Sutcliffe Simulation Efficiency (NSE), Relative Volume Error (RVE), Percentage Error Peak Flow (PEPF), and Mean Absolute Error (MAE). A common method of evaluating hydrological model performance and behavior is to compare computed and observed variables. The $R^2$ value represents the strength of the relationship between the observed and simulated values. The value of $R^2$ ranges from zero to one, with higher values indicating better agreement of simulated and observed values. The Nash-Sutcliffe Simulation Efficiency (ENS) displays the degree of fitness of the observed and simulated plots. The ENS also assesses how well the simulated results predict the measured data.

RVE indicates the variation between simulated and observed discharge on relative bases.The relative volume error can range between $-\infty$ and $\infty$ but it performs best when a value is zero showing there is no difference between simulated and observed discharge occurs.

The statistical indexes are given as:

$$R^2 = \frac{\left[\sum_{i=1}^{n}(Ysim-\bar{Y}\,sim)(Yobs-\bar{Y}obs)\right]^2}{\sum_{i=1}^{n}(Ysim-\bar{Y}sim)^2(\llbracket Yobs-\bar{Y}obs)\rrbracket^2} \tag{6}$$

where $Ysim$ is simulated discharge, $\bar{Y}sim$ is the average of simulated discharge, $Yobs$ is observed discharge, $\bar{Y}obs$ is the average of observed discharge ($m^3/s$).

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n}(Yobs-Ysim)^2}{\sum_{i=1}^{n}(Yobs-\bar{Y}obs)^2} \tag{7}$$

$$RVE = \frac{\sum_{i=1}^{n} Y_{sim} - \sum_{i=1}^{n} Y_{obs}}{\sum_{i=1}^{n} Y_{obs}} \tag{8}$$

Hence, the models were calibrated and validated using daily and monthly observed stream flow data obtained from MoWIE. For Bilate Watershed, the models were run from the simulation period (1999-2015). The first two years' data (1999-2000) were used for model initialization; the data for the next 10 years (2001-2010) was used for the model calibration and the remaining five years' (2011-2015) data was used for model validation. For the Gidabo Watershed, the data of one year (January1997-December 1997) stream flow was used for model warm-up; the data from 1998 to 2003 was used for model calibration and the remaining three years data (2004-2006) was used for the model validation. Both the HEC-HMS and SWAT models were automatically calibrated and validated at Bilate (Bilate Tena) and Gidabo (Measso) outlets. During calibration, sensitivity analysis was performed manually for the HEC-HMS model and automatically for the SWAT model using the SWAT CUP software's SUFI-2 program.

## 2.6 Model Uncertainty

### *2.6.1. Uncertainty analysis in the HEC-HMS model*

Uncertainty refers to the state of being uncertain about something. So far, there are four major sources of uncertainty in hydrologic modeling: (i) input uncertainty, e.g., sampling and measurement errors in catchment rainfall estimates; (ii) output uncertainty, e.g., rating curve errors affecting runoff estimates; (iii) structural uncertainty (model uncertainty) arises from a lumped and simplified representation of hydrological processes in hydrologic models and (iv) parametric uncertainty, reflecting the uncertainty in hydrologic models (Renard et al. 2010).

There are several approaches available to estimate uncertainty in hydrological models. The "Markov Chain Monte Carlo" approach was chosen for this investigation and incorporated in the present study. Convergence is attained when statistical measurements of the watershed response do not change as more samples are computed. The convergence of MCMC to a stable posterior probability density function (PDF) was monitored using statistics (Gelman & Rubin, 1992). Convergence is declared when $R \leq 1.2$ for all $j = 1$ d, where d represents the number of parameters. The calibration parameter constraints determine the simulated upper and lower bounds of the parameter (Scharffenberg, 2016). Finally, the upper, lower, and simulated hydrographs are plotted after determining the best upper and lower bounds for a hydrograph. The uncertainty is said to be low if most of the simulated hydrograph lies between the lower and upper bounds and high if the computed hydrograph lies outside the bound. As shown in equations 9, 10, and 11 below, the P-factor and R-factor are used to determine the strength of calibration/uncertainty of model parameters (Tegegne et al., 2019).

### *2.6.2. Uncertainty analysis in the SWAT model*

SUFI2 was chosen for this investigation because it converged with fewer iterations and allowed for resuming unfinished iterations and breaking iterations into multiple runs. The SUFI-2 algorithm, in particular, was well suited to the calibration and validation of the SWAT model since it incorporated all sources of uncertainty (Abbaspour et al., 2007). The P-factor, the percentage of measured data bracketed by the 95 percent prediction uncertainty (95PPU)., quantified the extent to which all uncertainties were accounted. As a result, the percentage of data captured (bracketed) by prediction uncertainty indicated our uncertainty strength of analysis. The 95PPU was calculated at the 2.5 % and 97.5 % levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling, with 5% of very bad simulations excluded.

The R-factor, the average thickness of the 95PPU band divided by the standard deviation of the measured data, was the other way to estimate the strength of a calibration and uncertainty analysis. As a result, SUFI-2 tried to bracket as much of the collected data as feasible with the smallest possible uncertainty band. The P-factor has a theoretical range of 0 to 100%, while the R-factor has a theoretical range of zero to infinity. A simulation with a P-factor of 1 and an R-factor of zero corresponds to measured data.

$$P = \sum_{i=1}^{T}(Z_t/T) * 100 \tag{9}$$

$$Z_t = \begin{cases} 1, & if\ Q_t^O \in (Q_{t,2.5\%}^S, Q_{t,97.5\%}^S) \\ 0, & Otherwise \end{cases} \tag{10}$$

where $Z_t$ has a value of 1 when the observed discharge is within the 95PPU interval; *t* is the simulation time step; $T$ is the number of time step in the observed data; $Q_t^O$ the observed data at time step t; $Q_{t,2.5\%}^S$, and $Q_{t,97.5\%}^S$ represent the simulated lower (calculated at the 2.5% level of the cumulative distribution) and higher (97.5% level) boundaries at time t, with S indicating the simulated data, and O observed data.

$$R_{factor} = \frac{avr(Q_{t,97.5\%}^S - Q_{t,2.5\%}^S)}{stdev\ of\ measured\ data} \tag{11}$$

## 3. RESULTS AND DISCUSSIONS

### 3.1 Sensitivity Analysis

The primary goal of sensitivity analysis is to describe how changes in model input values affect model outputs. Therefore, we performed sensitivity analysis manually to determine the most sensitive parameter in HEC-HMS. The sensitivity of the HEC-HMS model was evaluated using six key parameters from both watersheds. The results showed that constant rate (CR) and lag time (LT) were the most sensitive parameters. On the other hand, other parameters had no or only a minor impact on the model output (streamflow). Figure 4 shows the model-sensitive parameters.

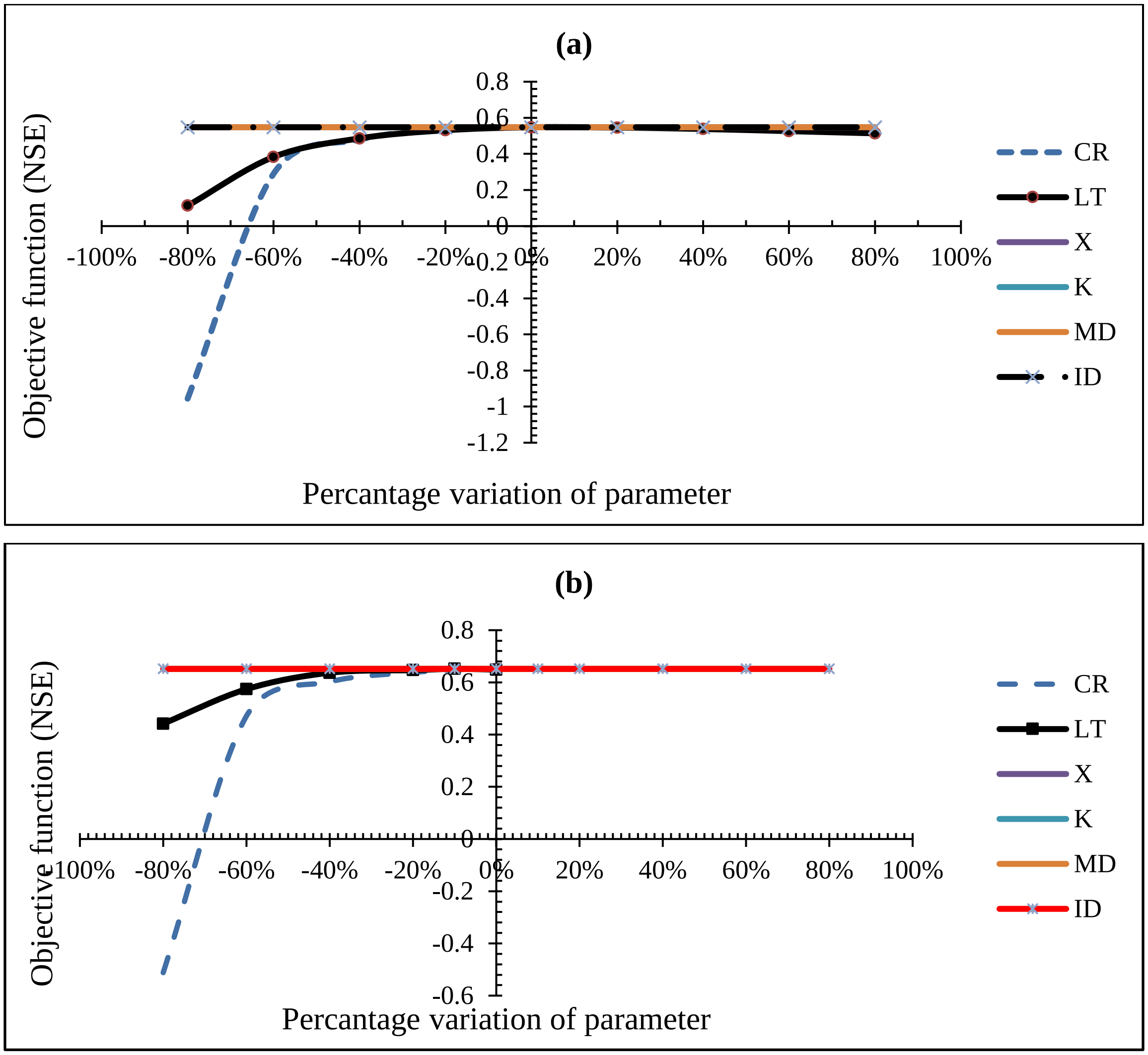



Figure 4. Model sensitivity using NSE in a) Bilate and b) Gidabo watersheds

In this study, we ran 1000 model runs in SUF-2 for sensitivity analysis. The sensitivity parameters were sorted based on the p-value and t-stat from the SUFI-2 sensitivity analysis. When the absolute value of the t-stat is significant, the parameter is more sensitive. At the same time, the p-value is closer to zero when the parameter is more significant. The results showed that the parameters governing subsurface water responses (ALPHA BF and GW REVAP) were found to be the most sensitive parameters in the Bilate Watershed, with a low p-value and a high absolute value of t-statistics. In the Gidabo Watershed, as represented in Figure 6, the relatively high sensitivity of CN-2 followed by SOL_AWC in the Gidabo Watershed indicated high runoff potential in the watershed. The lower soil layer had a greater capacity to hold water than the top soil layer. As a result, percolation of water and aquifer return flow might be restricted (Saha et al., 2014). This could be due to the variable properties of the input catchment. The curve number parameter (CN_2) arising from land use and antecedent soil water conditions was found to be the most sensitive model parameter, followed by SOL_AWC. The other parameters were found to be less sensitive in the simulation of stream flow. Figure 5 and Figure 6 shows the model sensitivity analysis and parameters in the SWAT model.

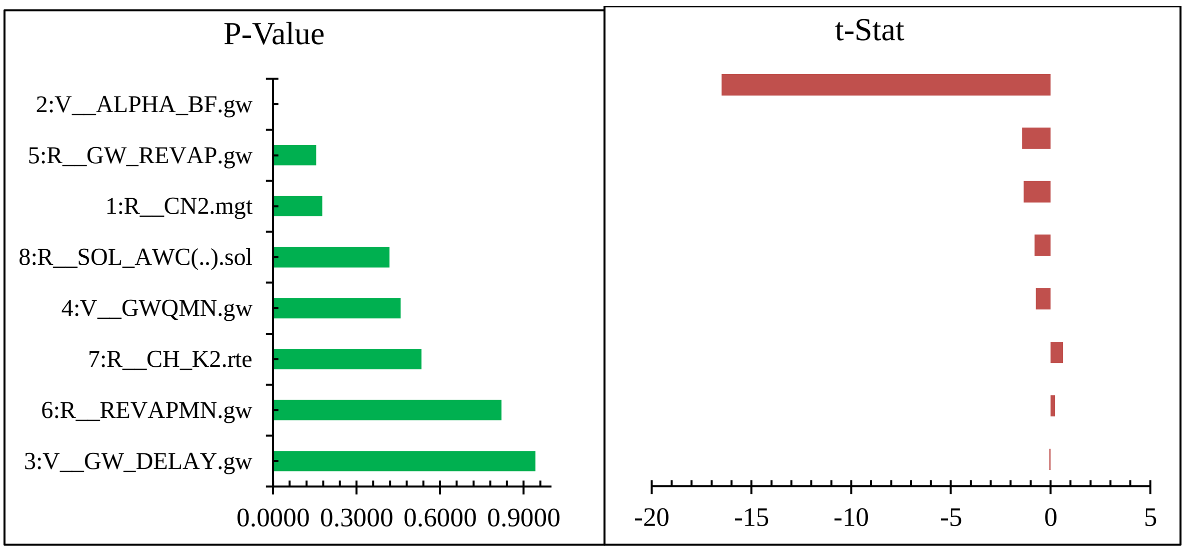



Figure 5. SWAT global model sensitivity for Bilate watershed

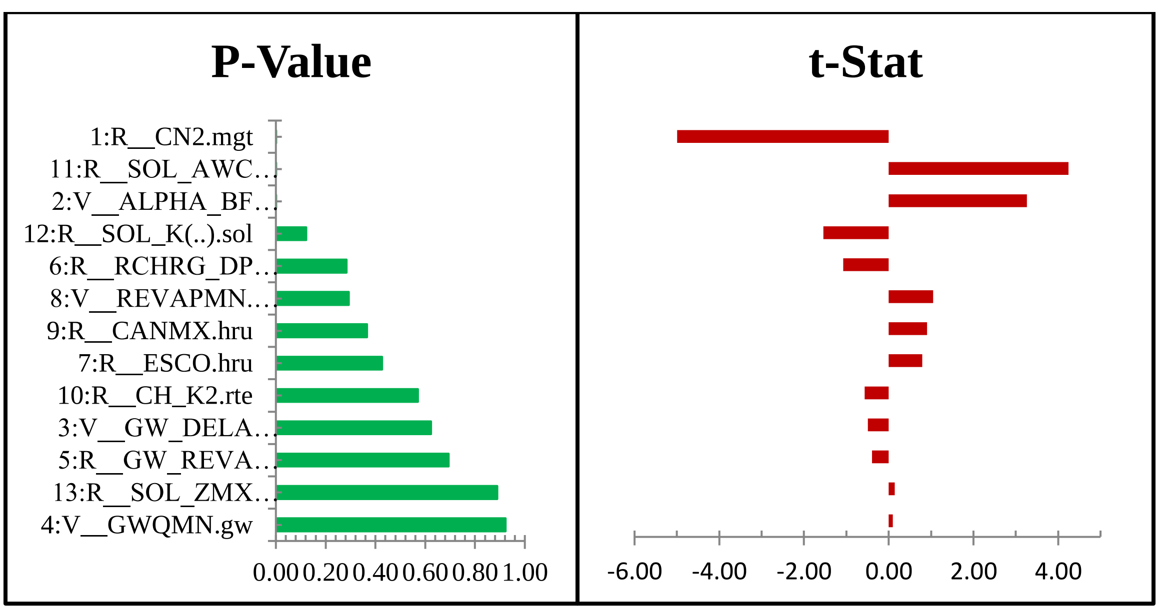



Figure 6. SWAT global model sensitivity for Gidabo watershed

## 3.2. Hydrological Model Calibration and Validation

Model calibrations were performed by fine-tuning the most sensitive model parameters within a given range in order to achieve agreement between simulated and observed stream flow in each watershed. The sections that follow describe the model calibration and validation efforts that were carried out using both hydrological models.

### *3.2.1. HEC-HMS model calibration and validation*

The parameters_ constant loss rate and lag time _showed significant variability in the rainfall-runoff modeling (HEC-HMS) of both watersheds during the calibration period. In contrast, routing parameters (K and X) remained constant. According to the volume relative error result in HEC-HMS, RVE was low in both watersheds, with absolute values less than 10%. In the Bilate and Gidabo watersheds, the mean magnitude of computed daily stream flow values was within a very good range (RVE>10). In terms of reproducing the observed pattern of daily stream flow during calibration and validation (NSE = 0.55) and coefficient of determination (R2=0.55), satisfactory performance was observed in Bilate Watershed. The response of Gidabo Watershed to the HEC-HMS model was better than that of the Bilate Watershed in all evaluation criteria performed in daily and monthly stream flow simulations. HEC-HMS performed well during calibration (NSE=0.65) and was satisfactory in the validation period (NSE=0.63). Similarly, the regression coefficient indicated that the simulated discharge was ($R^2$ =0.65) during the calibration and validation period. This showed the capability of the HEC-HMS model in simulating the observed stream flow hydrograph and the good correlation with observed flow data in the Gidabo Watershed. These HEC-HMS model results were consistent with previous studies in the Rift Valley Basin: HEC-HMS (Aliye et al., 2020; Kebede, 2017; Legesse, 2020). Table 1 shows the model calibrated parameters and their ranges for both watersheds.The percentage error in peak flow (PEPF) of HEC-HMS model was 68% in the Bilate Watershed and 21% in the Gidabo Watershed. The value of these measures confirmed that HEC-HMS captured peak flow in both watersheds satisfactorily. Furthermore, the mean absolute error of the HEC-HMS model was 0.63 in the Bilate Watershed and 0.04 in the Gidabo Watershed, indicating that the HEC-HMS models simulated with a lower mean absolute error during the calibration and validation period in both watersheds.

Table 1: Parameter range and their calibrated values for Bilate and Gidabo watersheds

| No | parameters | Bilate | | Gidabo | |
|---|---|---|---|---|---|
| | | Range | Fitted value | Range | Fitted value |
| 1 | Constant rate (CR) | 2.7-4.3 | 3.5 | 1.35-3.2 | 2.42 |
| 2 | Initial deficit( ID) | 0.1-2.3 | 1.89 | 0.001-2.1 | 2 |
| 3 | Maximum deficit(MD) | 2.8-5.8 | 5.7 | 2.11-2.99 | 2.5 |
| 4 | Lag time (LT) in min | 11000-13000 | 12000 | 25100-27400 | 26000 |
| 5 | Muskingum (K) | 0.1-145 | 1 | 125-145 | 145 |
| 6 | Muskingum (X) | 0.1-0.44 | 0.1 | 0.01-0.45 | 0.1 |

The relationship between daily observed and simulated streamflow hydrographs (Figure 6) was better in the Gidabo Watershed than in the Bilate Watershed. Because of the inspection, the performance of the model in simulating the hydrograph's base flow and rising and falling limbs was better in the Gidabo Watershed than in the Bilate Watershed.

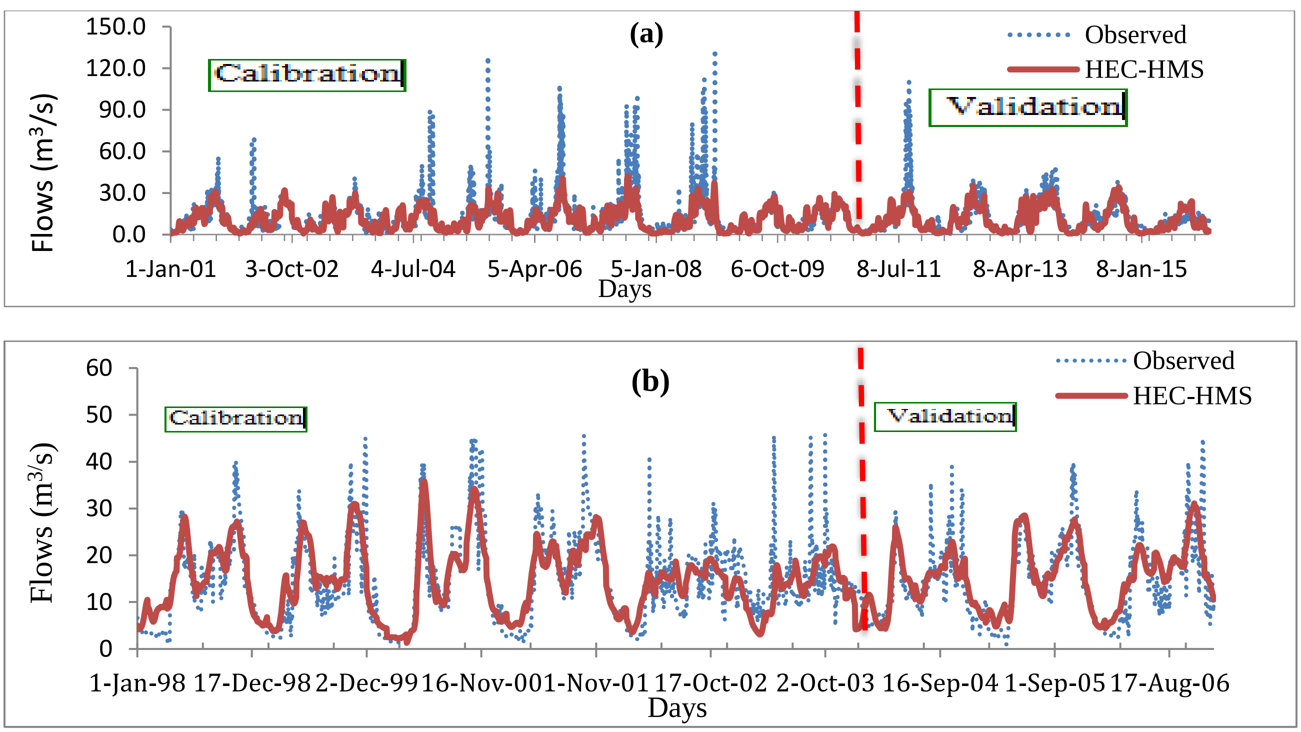



Figure 7. Daily observed and predicted stream flow hydrographs during the calibration and validation period for Bilate (a) and Gidabo (b) watersheds

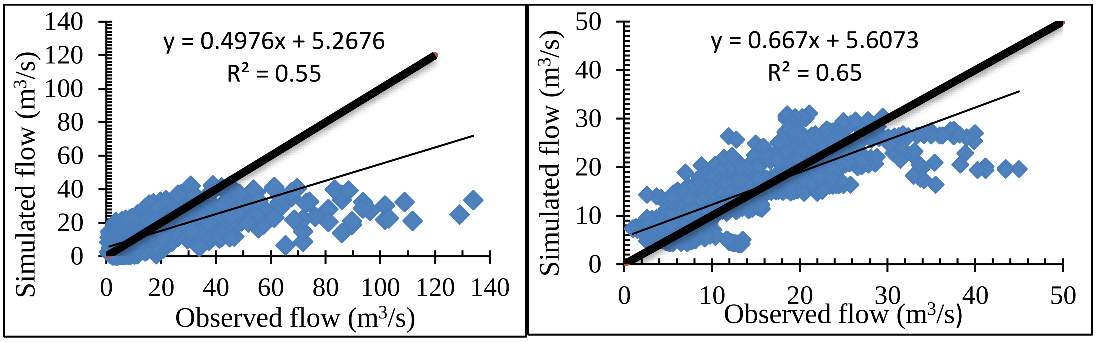
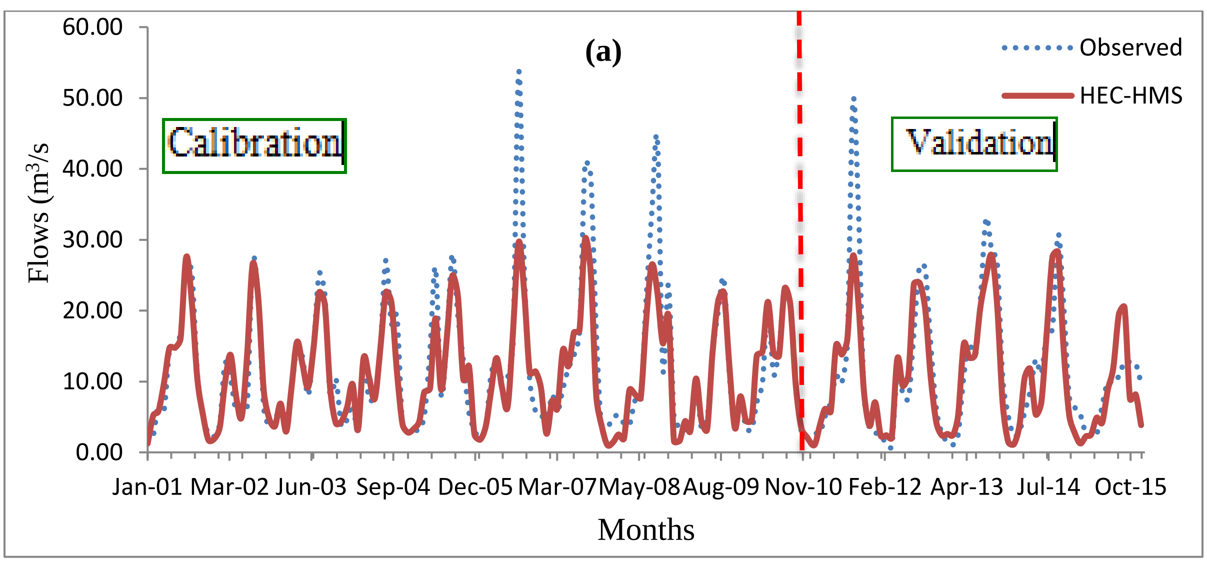



Figure 8. Scatter plot for the calibration Bilate (left) and Gidabo (right)

Figure 7 (left) illustrates a scatter plot of correlation analysis, demonstrating that more data are scattered below the 1:1 line in the Bilate Watershed, indicating that the model underestimated the predicted flow. On the other hand, the distribution values of Gidabo Watershed are over the 1:1 line as in Figure 7. It showed that the model slightly overestimated the stream flow. Hence, the model efficiency increased when the time step increased. As indicated in Figure 7, the observed and simulated hydrograph had a better mean monthly flow agreement than when the model was run for the daily time step. This is attributed to the hydrological models capturing less higher time resolution than lower time resolution. This is related to model uncertainty in model structure (Renard et al. 2010). Hence, the HEC-HMS model had limited capacity to capture the peakflow in both watersheds as indicated by PEPF.



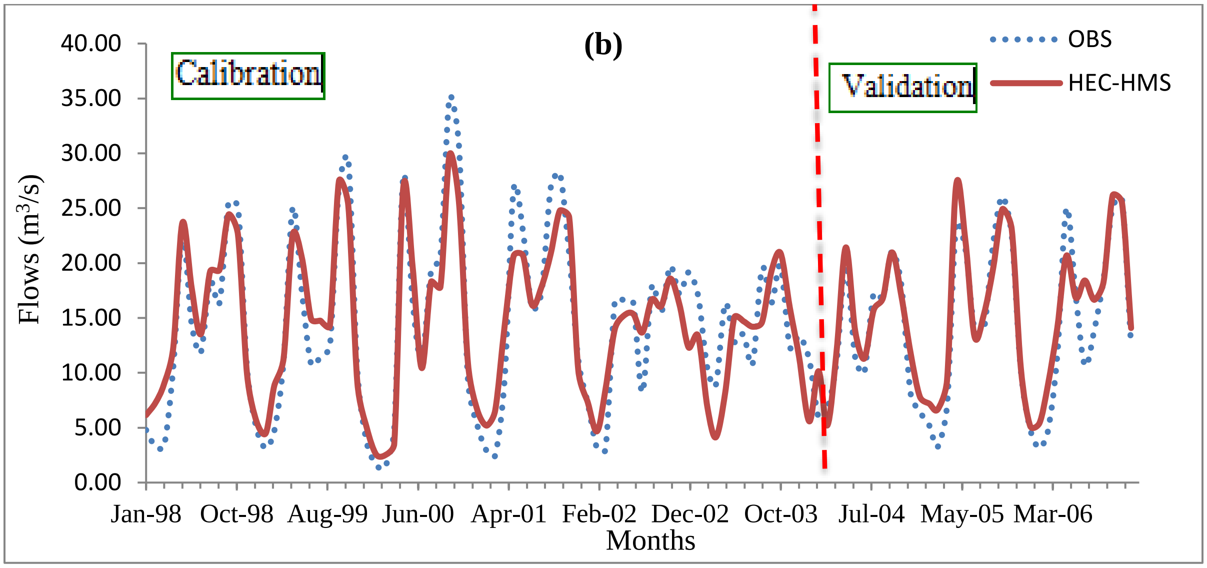



Figure 9. Monthly observed and predicted stream flow hydrographs during calibration and validation period for Bilate (a) and Gidabo (b) watersheds

### *3.2.2. SWAT model Calibration and Validation*

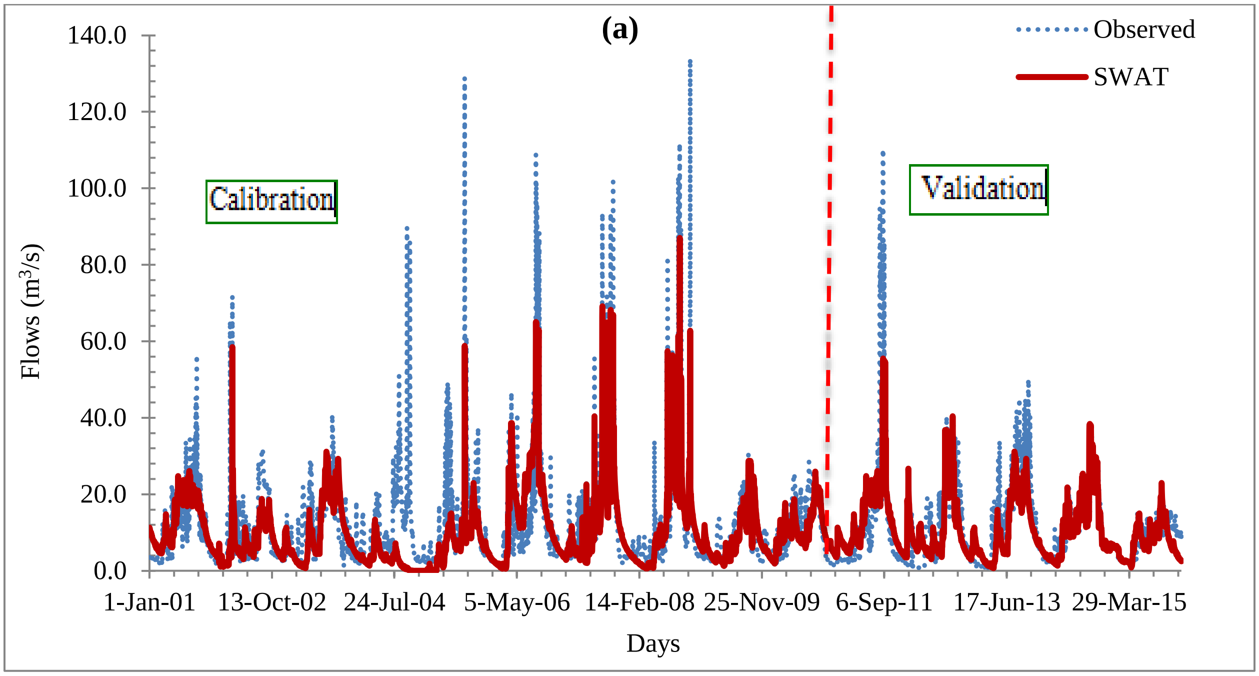
SWAT model enabled the observed daily stream flow to be reproduced during the model calibration and validation period (Figure 10). The observed and computed daily stream flow showed a 'satisfactory' agreement with NSE, RVE, and $R^2$ values varying in the range of 0.51 to 0.58, -14.5 to 1.3, and 0.52 to 0.61, respectively, for calibration and validation in both watersheds. Like HEC-HMS, the SWAT model performance can be rated as 'good' in both watersheds during the monthly calibration and validation (Figure 10) compared to daily streamflow simulation. Table 2 shows the calibrated-parameters and ranges for parameters.In addition, the percentage error in peak flow (PEPF) of the SWAT model is 35% in the Bilate Watershed and 18% in the Gidabo Watershed. These measures confirmed that SWAT captured the peak flow at both watersheds better than HEC-HMS. The error of the SWAT model was 1.7 in the Bilate Watershed and 0.19 in the Gidabo Watershed. This indicated that, the HEC-HMS models simulated with a lower mean absolute error than the SWAT model in both watersheds. Overall model performance on daily stream flow can be classified as "acceptable" during model calibration and validation periods based on evaluation criteria and (Moriasi et al., 2015; Rauf, 2018). In both watersheds during calibration and validation, the model performed with a greater agreement between observed and simulated monthly stream flow than daily stream flow simulation..

The statistical values were better on a monthly time scale in both models (HEC-HMS and SWAT) because monthly values were the mean of the physical phenomena, and models were good for average conditions compared to extreme events. Moreover, in monthly time steps, the differences that affected the hydrologic processes on a smaller temporal time step were smoothened.

Table 2. SWAT model calibrated parameters for Bilate and Gidabo watersheds

| Parameters | Effect of parameter when its value increase | Recommended range | Fitted value | |
|---|---|---|---|---|
| | | | Bilate | Gidabo |
| ALPHA_BF | Increase the ground water flow response to changes in recharge | 0-1 | 0.01953 | 0.0001 |
| CN2 | Increase surface runoff | 35-98 | 0.25560 | 1.7406 |
| Groundwater | Decrease base flow | 0-5000 | 5.48984 | 840.50 |
| ESCO | Decrease evaporation | 0-1 | * | 0.0059 |
| SOL_AWC | Increase groundwater recharge | 0-1 | 0.95752 | 0.7972 |
| CANMAX | Increase the canopy water trapping and storage | 0-10 | * | 0.4716 |
| REVAPMN | Decrease the actual amount of water moving into the soil zone in response to water deficiencies | 0-500 | 165.589 | 0.1659 |
| GWREVAP | Decrease base flow by increasing water transfer from shallow aquifer to root zone | 0.02-0.2 | 0.06791 | 0.3193 |
| SOL_ZMAX | Maximum rooting depth of soil profile | 0-3500 | * | 0.5005 |
| SOL_K | Saturated hydraulic conductivity | 0-2000 | * | 93.391 |
| GW_DELAY | Groundwater delay time | 0-500 | 2.34398 | 2.5089 |
| CH_K2 | Effective hydraulic conductive of main channel | 0-500 | 113.742 | 0.7362 |
| RCHRG_DP | Deep aquifer percolation fraction | 0-500 | * | 0.0014 |

**Indicate the parameters are insensitive and not significant in Bilate watershed*



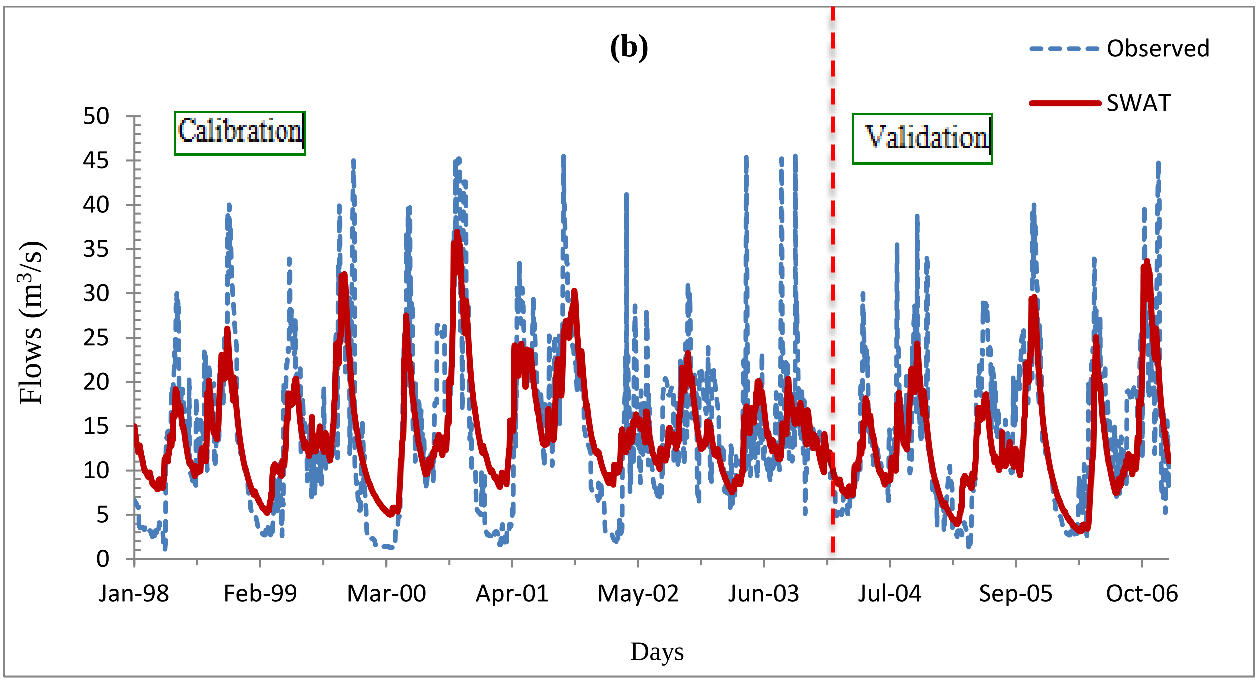




Figure 10. Daily observed and simulated stream flow hydrograph during calibration and validation periods for Bilate (a) and Gidabo(b) watersheds

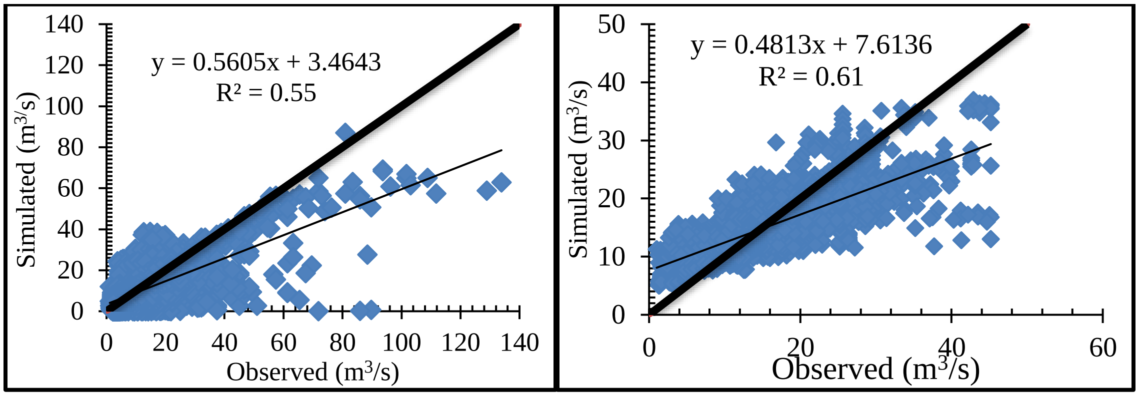



Figure 11. Scatter plot for the calibration Bilate (left) and Gidabo (right)

The observed versus simulated scatter plot in Figure 10 (left) showed more values distributed below the 1:1 line, indicating that the model underestimated simulated flows in the Bilate Watershed. In contrast, the distributed values simulated flows in the Gidabo Watershed (right) were above the 1:1 line, indicating that the model slightly overestimated simulated flow.

The statistical result of the SWAT model on daily stream flow for Nash Sutcliffe coefficients (NSE), coefficient of determination ($R^2$), and relative volume error (RVE) in the Bilate Watershed were 0.53, 0.55, and -14.45%, respectively. The statistical values indicated that the model could satisfactorily simulate the daily stream flow to Bilate Watershed response. Figure 9 showed a close agreement between observed and simulated peak flow levels during calibration ($R^2$=0.61) in Gidabo Watershed. The Nash criteria produced better outcomes between the simulated and observed streamflow (NSE=0.58), with a Relative Volume Error (RVE) of 1.31%. The relative volume error resulted in a very good outcome because the relative percent errors between the observed and simulated values were less than 5%. The simulated model performance findings for the SWAT model in this study were compatible with Tolera, 2012; Mohammed et al., 2020; Tewodros, 2012; and Golmar et al., 2014.

The percentage error in the peak flow (PEPF) of the SWAT model was 35% in the Bilate Watershed and 18% in the Gidabo Watershed. This confirms that SWAT captured peak flow at both watersheds better than HEC-HMS. The average error of the SWAT model was 1.7 in the Bilate Watershed and 0.19 in the Gidabo Watershed, which indicated that the HEC-HMS models simulated a lower mean absolute in both watersheds error than that of the SWAT model.

SWAT model was also used to build user confidence in the predictive capabilities of the model. As a result, the model was validated using daily data collected from both watersheds. During validation, the performance of the modelwas evaluated using $R^2$, NSE, and RVE. The statistical values in the validation period were ($R^2$=0.54), (NSE=0.52), and (RVE=-6) for the Bilate Watershed and ($R^2$=0.6), (NSE=0.56), and (RVE=11) for Gidabo Watershed at the daily time step.

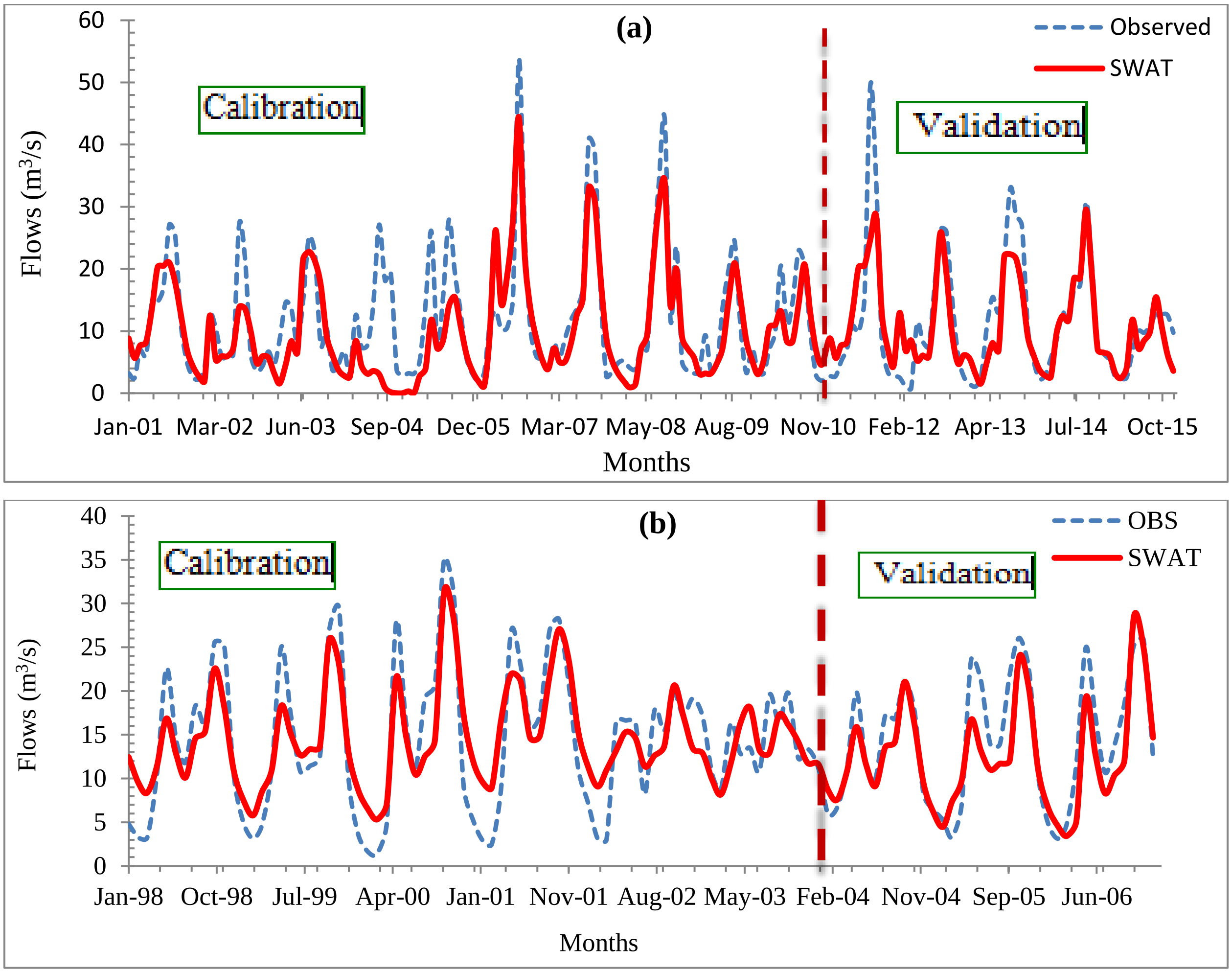



Figure 12. Monthly observed and simulated stream flow hydrograph during calibration and validation periods for Bilate (a) and Gidabo(b) watersheds

### 3.3. Comparison between HEC-HMS and SWAT Models in Simulating Stream Flow

Both models were compared for daily and monthly stream flow simulation. The two hydrological models differed in terms of runoff generation mechanisms, as well as model concepts and structures. When the models' overall performance was evaluated, both models were capable of reproducing the stream flow adequately. Table 3 shows the statistical indices used to evaluate the model performances in both watersheds.

As per Moriasi et al. (2015), the two models were sufficient in terms of matching the observed pattern of stream flow hydrographs in both watersheds. Meanwhile, as evaluated by the coefficient of determination ($R^2$), both models in the Bilate Watershed exhibited an acceptable correlation between observed and simulated flow peaks. HEC-HMS showed good performance in the Gidabo Watershed whereas SWAT model performed satisfactorily in the same watershed. Despite their similar modeling capabilities, a comparison analysis revealed that the HEC-HMS model was better in predicting the overall variation of stream flow for both watersheds. This may be attributed to the fact that SWAT needed more input variables and parameters than HEC-HMS. SWAT model simulations might have probably drawn many uncertainties and hence reduced the model performance during model calibration and validation times. It should be noted that the model uncertainties were also related to model inputs which a modeler could not easily identify. Input variables are acceptable and perfect despite having uncertainties as described by Renard et al. (2010). Similar observations were made by Aliye et al. (2020). Ismail et al. (2020) who simulated streamflow using the HEC-HMS model found that HEC-HMS was better than the SWAT model. Despite the performance of each model that differed from watershed to watershed, the selected models performed relatively better in the Gidabo Watershed than in the Bilate Watershed. This may be attributed to factors influencing runoff generation in both watersheds, including land use and land cover, climatic conditions (mainly rainfall characteristics), morphometric conditions, and soil. The Gidabo Watershed had a small area covered by forest whereas the Bilate Watershed had no forest land use.. On the other hand, the catchment area of Bilate was well above that of Gidabo, and its slope range was comparatively high. Therefore, a relatively average condition of hydrologic response was possible compared to hydrologic responses in the Bilate Watershed. This would favor hydrologic models to simulate responses better. However, future investigation of hydrologic responses and enforcement of variables concerning hydrologic models' capability should be done to capture these events. The HEC-HMS was a suitable and sufficient model for simulating daily and monthly stream flow compared to SWAT.

HEC-HMS consistently underpredicted peak flows. Ismail et al. (2020) also discovered that the HEC-HMS model was unable to model peak flows. (Meenu et al., 2010) agreed with this study because HEC-HMS was unable to replicate peak flows. SWAT was found to be more effective than HEC-HMS in capturing targets in both watersheds over daily and monthly time intervals.

Table 3. Statistical indicators to evaluate the performance of models for daily and mean monthly time steps in Bilate and Gidabo watersheds

| Watershed | Model | Process | Statistical Index | Daily | description | Monthly | Model performance |
|---|---|---|---|---|---|---|---|
| Bilate | HEC-HMS | Calibration | NSE | 0.54 | satisfactory | 0.79 | Good |
| | | | R^2 | 0.55 | satisfactory | 0.81 | very good |
| | | | RVE | -5.39 | good | -5.31 | good |
| | | Validation | NSE | 0.55 | satisfactory | 0.72 | Good |
| | | | R^2 | 0.55 | satisfactory | 0.73 | Good |
| | | | RVE | -6.94 | good | -6.49 | good |
| | SWAT | Calibration | NSE | 0.53 | satisfactory | 0.62 | satisfactory |
| | | | R^2 | 0.55 | satisfactory | 0.65 | good |
| | | | RVE | -14.46 | good | -14.45 | satisfactory |
| | | Validation | NSE | 0.51 | satisfactory | 0.68 | good |
| | | | R^2 | 0.52 | satisfactory | 0.65 | good |
| | | | RVE | -6.01 | good | -5.74 | good |
| Gidabo | HEC-HMS | Calibration | NSE | 0.65 | good | 0.85 | very good |
| | | | R^2 | 0.65 | good | 0.86 | very good |
| | | | RVE | 0.46 | very good | 0.5 | very good |
| | | Validation | NSE | 0.63 | good | 0.86 | very good |
| | | | R^2 | 0.65 | good | 0.88 | very good |
| | | | RVE | 6.02 | good | 6.59 | good |
| | SWAT | Calibration | NSE | 0.58 | satisfactory | 0.73 | good |
| | | | R^2 | 0.61 | good | 0.77 | good |
| | | | RVE | 1.3 | very good | 0.49 | very good |
| | | Validation | NSE | 0.56 | satisfactory | 0.73 | good |
| | | | R^2 | 0.6 | good | 0.78 | good |
| | | | RVE | -11.41 | good | -11.44 | good |

### 3.4. Model Uncertainty

Uncertainty analysis helps understand the predictive power and limitations of a model, , and make informed decisions. According to Sánchez et al. (2015) uncertainty analysis is the formal process of defining a model and mapping it onto model output uncertainty, thereby measuring the range of possible outcomes.

The MCMC approach reduced the source of uncertainty resulting from parameters in HEC-HMS. The convergence of MCMC to stable posterior probability density function (PDF) was monitored by using statistics (Gelman and Rubin, 1992). The P-factor and R-factor were used to determine the strength of model calibration and uncertainty (Abbaspour, 2014). The P and R factors of Bilate Watershed were 0.34 and 0.1, respectively. In the Gidabo Watershed, they were 0.34 and 0.22, respectively. According to the uncertainty analysis results, the number of goodness-of-fit criteria (NSE, RVE, and $R^2$)was within acceptable limits. As a result, the parameters used to simulate streamflow in the Bilate and Gidabo watersheds using HEC-HMS with input data were valuable and useful for future research (Figure 13).

SWAT CUP uses SUFI-2, an essential tool for continuous iteration, to help understand uncertainty in the SWAT model. In SUFI-2, all the uncertainty sources were not separately predicted but considered total model uncertainty to the parameters. The P and R factors were used from the 1000 model runs simulated in SUFI-2 to define how much of the simulated hydrograph brackets observed streamflow. A P-factor of 0.46 and an R-factor of 0.40 was obtained during calibration in the Bilate Watershed . In the Gidabo Watershed, the P-factor and R-factor were 0.80 and 0.88, respectively. Because the P and R factor values were in the optimum range, the goodness-of-fit of the model was reasonably acceptable (Figure14).

Regarding model prediction uncertainty, MCMC in HEC-HMS predicted the smallest uncertainty band in both watersheds compared to SUFI-2 in SWAT. This was because MCMC in HEC-HMS would not account for input data and model structure uncertainty, resulting in an underestimation of prediction uncertainty (Zhang et al., 2015). Furthermore, the parameter uncertainty predicted by MCMC only accounted for a small portion of the total uncertainty, whereas SUFI-2 considered all sources of uncertainty, resulting in broader parameter ranges. Therefore, model prediction uncertainty analysis and parameter uncertainty value ranges were reasonably acceptable (Abbaspour, 2014)

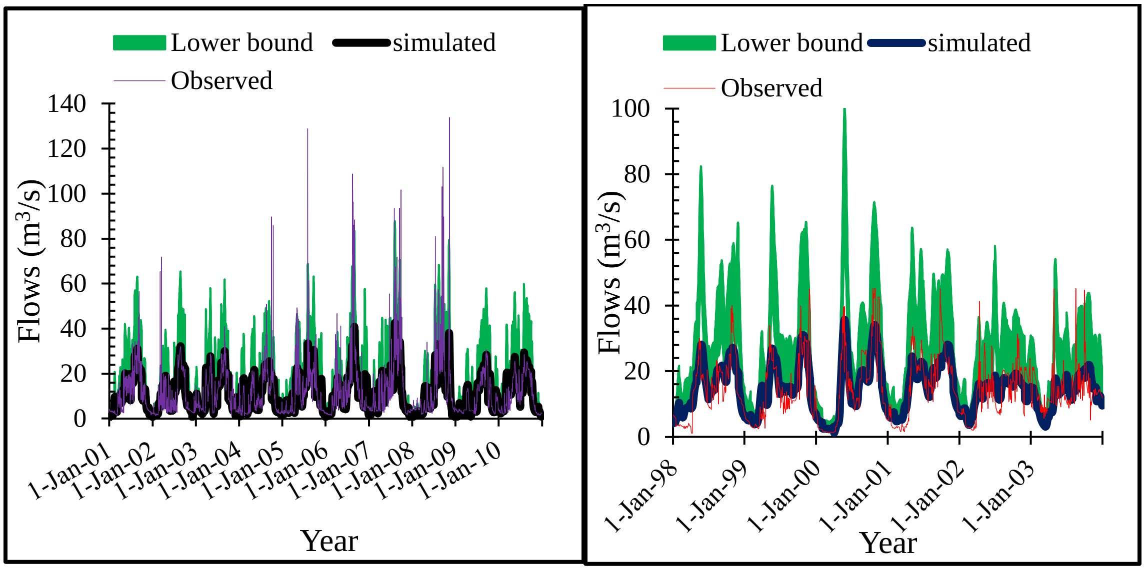



Figure 13: Uncertainty analysis in HEC-HMS model Bilate (left) and Gidabo (right)

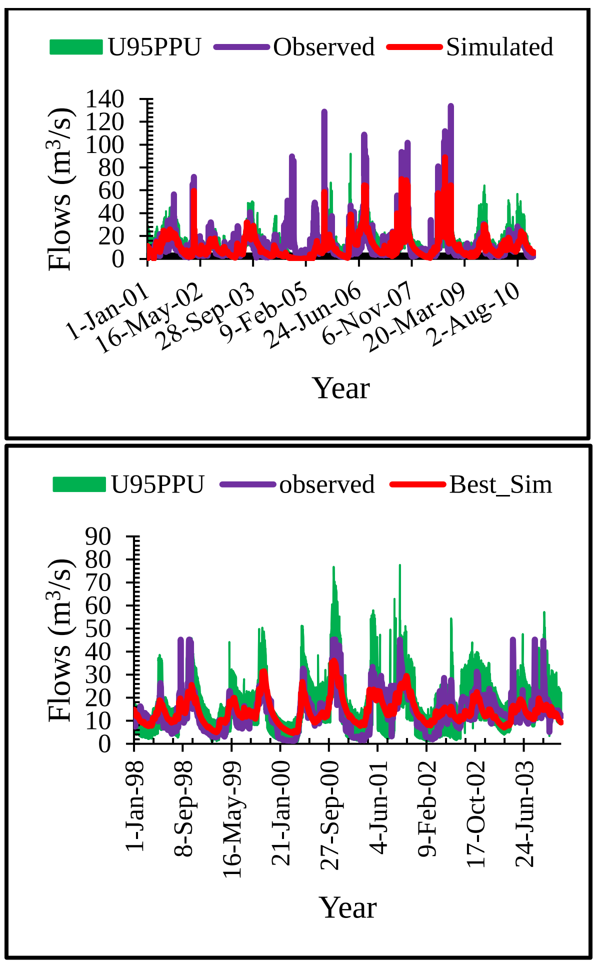



Figure 14: Uncertainty plot for SWAT Bilate (left) Gidabo (right) watershed

## 4. CONCLUSION

This study compared the performance of the HEC-HMS and SWAT models in stream flow simulation to determine the best model for the Bilate and Gidabo watersheds. Observed stream flow at the outlets of the Bilate and Gidabo watersheds were used for comparison. It was discovered that the performance of both models was superior in both watersheds. However, in both watersheds and for daily and monthly time steps, the HEC-HMS hydrological model outperformed the SWAT model. Furthermore, the HEC-HMS model was predicted to outperform the Bilate watershed in the Gidabo Watershed. As a result, the HEC-HMS hydrological model would be preferred to the SWAT hydrological model. In fact, due to the economics of hydrological modeling, the need for model input data in SWAT pushes it aside. Hydrologists are advised to look for the HEC-HMS model in general, and the Gidabo Watershed in particular, unless specific needs and high accuracies are not deemed necessary based on detailed input data.The uncertainty analyses also favored the HEC-HMS model, which predicts stream flow response with less uncertainty. This research will be beneficial to future hydrologists and practitioners.

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## Conflict of Interest

There is no conflict of interest related to this manuscript.

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